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A new texture descriptor for handwritten document writer identification

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ABSTRACT

Writer identification is a critical task in the realm of pattern classification, aimed at determining the authorship of a manuscript based on labeled handwriting samples. This area has garnered considerable attention from researchers and has seen significant advancements in the last two decades, propelled by the integration of novel computer vision and machine learning algorithms. Commonly, approaches within this field rely on calculating local texture descriptors of images. In this work, we propose a novel local texture descriptor method, termed multi-points local binary patterns (MP-LBP), which is an enhancement of the traditional local binary patterns (LBP) descriptor. Our approach involves applying the MP-LBP descriptor to patches surrounding Harris key points and aggregating the image descriptors into encoded vectors using the vector of locally aggregated descriptors (VLAD) encoding method. These vectors are subsequently classified by a ball tree classifier to associate the document with the most plausible writer. To assess the efficacy of our descriptor, we conducted evaluations on five publicly accessible handwritten databases: CVL, CERUG-EN, CERUG-CH, BFL, and IAM. The results of these tests provide insights into the performance of the MP-LBP descriptor in the context of writer identification.

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1. INTRODUCTION

Writer identification poses a significant research challenge. Over the past two decades, the research community has devoted substantial efforts to addressing this challenge, particularly in scenarios involving cursive and disjoint writing styles. In the field of handwriting analysis, two distinct research areas are recognized: handwriting recognition and writer recognition. Handwriting recognition focuses on deciphering the content of handwritten text within a document, irrespective of the writer. On the other hand, writer recognition addresses two key aspects. Firstly, writer verification aims to determine whether two or more handwritten documents are authored by the same writer. Secondly, writer identification pertains to techniques that enable the identification of the author of a given document from a known set of writers. Writer identification focuses on invariants in the writings of each writer [1] (features). This assumes that, when writing, an individual draws characters using his unique basic shapes. Thus, identifying the writer of a given document relies on these writer-dependent characteristics.

The hand writing is considered as a reliable behavioral biometric [2]. In fact, each individual devel-

ops his proper writing style. Over time, the writing style becomes more stable. Finding the authorship of the documents from scanned handwritten images is useful in historical document analysis and forensics. In the historical document analysis to verify a manuscript authenticity, and in forensic to help investigators to find suspects by analysing their manuscripts such as threatening letters, wills or ransom notes [3], [4]. The handwriting analysis can also be useful for determining the gender of the writer [5], as it can help to determine the true writer of a manuscript based on documents written in another language [5], [6].

The writer identification approaches can be divided into text-dependent and text-independent mode. Text-dependent [7] method requires all writers to produce the same text. Whereas in text-independent mode [2], [8], the writers produce arbitrary textual content. This last scenario appears a more realistic scenario. From another perspective, writer identification can be achieved in either online and offline mode. In the offline mode, we are working with digitized versions of the handwritten documents. Whereas in the online mode, the writers use an electronic pen which allows to capture more characteristics such as pen pressure and speed, and thus provides additional insights for writer identification [9]. Researches in the field of writer identification become even more challenging as an individual writing style depends on other noisy factors such as their mental condition, pen thickness, and writing environment.

In the offline writer identification, we proceed generally in three main phases: the first one consists in pre-processing the handwritten images. The second phase is feature extraction, where we extract the feature vectors of the images. Finally, the classification phase allows to assign a test document to its appropriate writer based on its extracted feature vectors and using the classification algorithm such as support vector machine (SVM) [10]-[12], k-nearest neighbors (KNN) [13], X2 distance [2], vector of locally aggregated descriptors (VLAD) [14], and Chi-square distance similarity [15].

In this paper, we address the problem of offline text-independent writer identification through introducing a new local texture descriptor. For this purpose, we organized this paper in six sections. In the next section, we will present a survey of existing works. In section 3, we will describe the proposed methodology. In section 4, we present the datasets that we used for tests and experiments. While section 5 presents the test results and comparison with state-of-the-art works. Finally, section 6 concludes the study and proposes some future directions.

2. RELATED WORK

As the handwritten analysis seems tedious and time consuming procedure for human examiners, developing automated systems for handwriting analysis has become necessary. Such a solution should identify a writer using less amount of writing and in a short time. In this sense, many computerized solutions based on artificial intelligence were created. In these solutions, the writer identification problem is dealt as a pattern classification problem [16], [17].

One of the earlier works in automated writer identification is the one of Arazi [18] that dates back to 1977. The author proposed a run-length histogram descriptor, which is described as a performant global descriptor. Since then many studies have been realized. In the literature, the researchers have adopted many approaches in order to address the writer identification problem. Indeed, some works used a global features approach, which consists in studying overall characteristics at the document or paragraph level, such as line separation and skew [19]-[21]. While other works used local characteristics features witch correspond to allograph, character or shape level of the handwriting contours [22]-[25] to characterize the writer. At that level, different works used local descriptors local binary patterns (LBP) [24], [26], [27], local phase quantization (LPQ) [24], [26]. In 2014, Newell and Griffin [28] used oriented basic image feature columns (OBIF) and delta encoding to enhance texture-based approach. OBIF was used later in many other works [21], [29]. Numerous other descriptors are also reported in the literature: run length [10], edge-hinge [10], edge-direction [10], local ternary patterns (LTP) [30], contour-direction [2], contour-hinge [2], or histogram of oriented gradients (HOG) [30]. As our proposed multi-points local binary patterns (MP-LBP) texture descriptor is based on LBP, it is worth noting that many works have used LBP texture descriptor in writer identification field, and realized different identification performance.

LBP descriptors were first used in writer identification in 2002 by Ojala *et al.* [31]. LBP descriptor were also used by Bertolini *et al.* [26]. In their approach, the writers used the LBP and LPQ texture descriptors. In this study, the writers found that the discriminatory power of LPQ descriptor surpasses that of LBP. The performance of their approach is reflected in the identification scores: 96.4% and 98.9% obtained using,

respectively, the two datasets Qatar University Writer Identification-Arabic (QUWI-AR) and Qatar University Writer Identification English (QUWI-EN).

In 2015 Hannad *et al.* [32] published their work on writer identification using the LBP texture descriptor. Their method achieved an identification rate of 87% on the IFN/ENIT datasets. The interesting results have proven again that using LBP in writer identification not only enhances the scores but also reduces the execution time compared to other methods [33].

Hannad *et al.* [24] used LBP, LTP, and LPQ calculated on small fragments of the hand written documents. In this study, the writers emphasize also the importance of choosing good values of fragments' size parameter. For example, choosing the size 100x100 for IFN-ENIT dataset, and 110x110 for IAM, they obtained the respective scores 94.9% and 89.5%. One other work using LBP descriptor is the one of Singh *et al.* [34]. This study compares performances of different descriptors. Indeed, the tests performed on KHATT and IAM datasets showed that LBP and LPQ performance (95.6% and 97.6%) realized the best scores when compared to the other descriptors. In 2019 Bennour *et al.* [35] introduced the key points in handwriting while using a codebook approach.

Abbas *et al.* [29] published a more recent approach based on the crossing of multiple configurations LBP model. The tests, carried out on BFL and KHATT datasets, realized respectively the scores 98.6% and 77.1%. Other researchers have proposed codebook-based graphemes systems [36] or codebook-based small fragments [37] systems. Recently, many research works have tackled the writer identification problem using deep learning and convolution neural network [9], [38]-[42]. Using deep learning in writer identification allows to achieve better identification results. However, ne major inconvenient of using deep learning is that it requires high processing power and storage capacity, and an extended computation time that can exceed several weeks [43]. From another perspective, the works in the literature having used LBP, and other textural descriptors, extract features at different document levels. Indeed, for [2], [10] the features are extracted at the whole document level. Whereas for [26], [34], [44]-[47] the features are extracted at the regions of interest level. These regions may correspond to blocks, cells, or words. Another working level corresponds to writing fragments [24], [30], [48]. In 2019, Bahram [49] found that the LBP histograms, when calculated at page or paragraph level, give only an overall view of the document texture and allow a low performance in detecting discriminatory details. However, the identification performance is improved when the texture features are calculated at the level of connected-component.

3. METHODOLOGY

In this section, we present the different phases of our approach, which consists of the following: we first start by pre-processing the handwritten document images, and then we identify the locations of the key points. For each key point, we define a fixed-size window around it. We then extract the features using our proposed texture method (MP-LBP). The image features are subsequently encoded with a VLAD method. Finally, we assign the the test document to the most plausible writer using a KNN and ball tree algorithm. These phases are illustrated in Figure 1.

3.1. Pre-processing

The training and test images are initially retrieved from stored image files. Pre-processing for each image involves two steps: i) converting the image to a grayscale format and ii) applying a de-noising Gaussian filter [50] to the intensity image to remove any background smudges or noise that can obstruct writer identification. Our image pre-processing does not involve the skew and slant corrections. The different algorithms are implemented using opencv and other Python libraries.

3.2. Key points detection

In computer vision field, “key point” term refers to a specific location in the image where the boundary of an object changes direction abruptly. In our work we used Harris keypoints detector [51]. Harris is a powerful and widely used detection method. The concept of Harris method consists in computing the difference in pixel brightness when moving a sliding window in the different possible directions as illustrated in Figure 2.

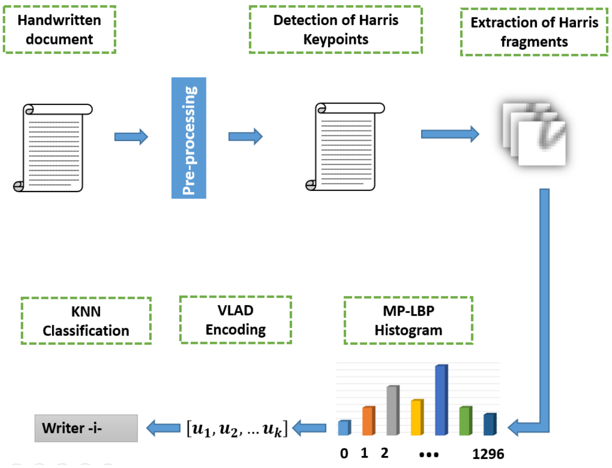

Figure 1. The proposed methodology

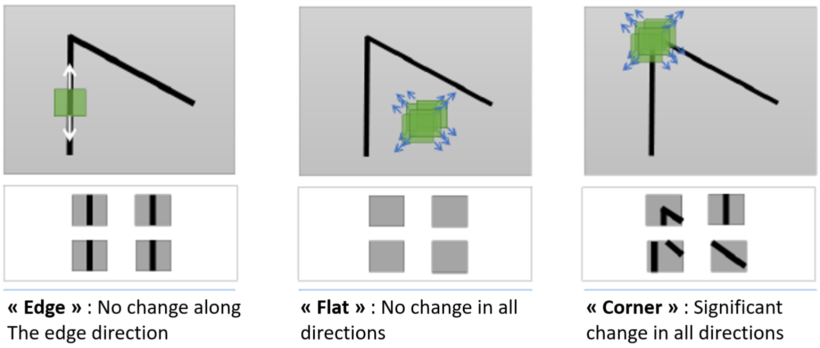

Figure 2. Harris corner detector method

3.3. Feature extraction

The handwriting characteristics are broadly measured by a number of geometric features, such as global statistics of ink traces [2], [3] or the distribution of graphemes [22], [52]. Feature extraction from images aims at reducing the big amount of data in the raw images to a smaller and concise set of parameters. In this phase, local features (descriptors) are calculated on small square windows centered around the key points that we obtained in the previous phase. Other works used descriptors that are calculated on random non-overlapping windows extracted from the image [53], or using an adaptive window-positioning algorithm [54]. Before introducing our proposed texture method, which is a generalization of LBP [24], operator, we will, first, present the classic LBP method.

3.3.1. Local binary pattern descriptor

LBP operator assigns binary code to each pixel based on its surrounding. Indeed, LBP is obtained by comparing the intensity of the pixel with the ones of its P neighbors in a circle of radius R. Then it calculates the sum of the obtained values weighted by powers of 2. Given a pixel at the position C in the Figure 3, the resulting LBP is obtained using (1):

$$LBP\left(C\right) = \sum_{i=0}^{P-1} s(g_i - g_c)2^i \tag{1}$$

g_c and g_i are respectively the intensity of the central pixel c and the i^{th} neighbor. s(x) is the function defined as:

$$s\left(x\right) = \begin{cases} 1, & if\ x\geq 0 \\ 0, & otherwise \end{cases}$$

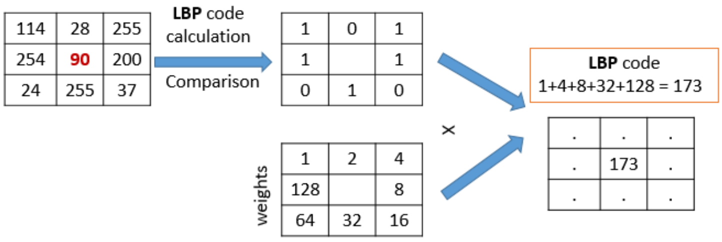

Figure 3. LBP code calculation

3.3.2. Multiple-points local binary patterns descriptor

LBP descriptor consists on one-to-one comparison of pixel intensities. Indeed, when comparing the intensity of a central pixel g_c to the one of its P neighbors $(g_i)_{0<=i<p}$ the comparison returns two possible values: either g_i is greater than g_c or not, this is why we use the power of 2 to encrypt the different possible cases. In our new approach, we compare the intensities of 3 pixels instead of 2: each time we compare the central g_c with two other chosen pixels a_i and b_i. A combinatory reasoning indicates that the cardinality of the comparison space relative to three elements comprises $3! = 6$ possibilities. Thus, powers of 6 instead of 2 are used to encode the obtained comparison results. An example of the 6 possibilities (comparison space) is the one corresponding to the case: $a_i > g_c >$ b$_i$.

The resulting MLBP for a pixel C is:

$$MP-LBP\,(C) = \sum_{i=0}^{P-1} s(a_i,\ g_c,\ b_i) * 6^i$$

The function $s(g_i,\ g_c,\ g_j)$ allows to map each element of the comparison space, that is calculated based on the comparison of the three intensities a_i, g_c and b_i with an element of the set $\{0, 1, .. ,5\}$. Table 1 shows the values of the function s for all the possible cases.

Table 1. Mapping function

A>B	B>C	A>C	s(A,B,C)
0	0	0	0
0	1	0	1
0	1	1	2
1	0	0	3
1	0	1	4
1	1	1	5

In the LBP approach, the neighbors that are compared to a central pixel are a set of individual points. Whereas for our MP-LBP descriptors, each comparison i involves, besides the central pixel C, a pair of neighbors Ai and Bi. The pixel $(\mathrm{A}_i)_i$ and $(\mathrm{B}_i)_i$ are chosen using the proposed pattern shown in Figure 4 which defines the distance and the form of the chosen surrounding pixels. As for LBP descriptor, our MP-LBP is also insensitive to variations in illumination Figure 5.

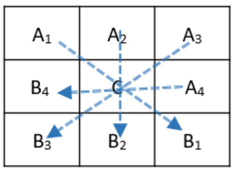

Figure 4. The pattern used in MP-LBP

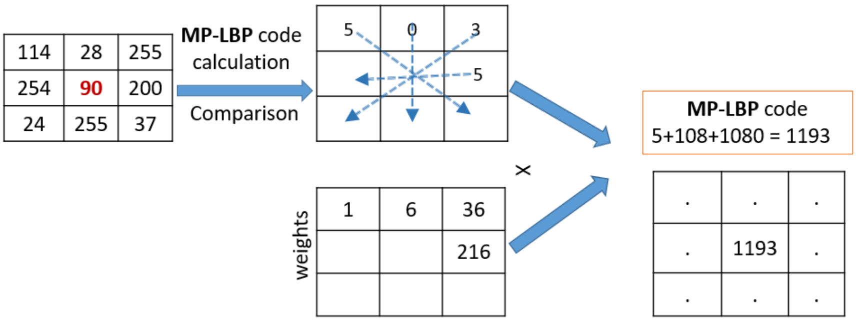

Figure 5. MP-LBP code calculation

3.4. Vector of locally aggregated descriptors feature encoding

Before encoding the features of the handwritten documents, we first start by clustering (i.e. grouping) all the local descriptors of the training and test documents. As the total number of descriptors is too big, (e.g. about 6 million for IAM dataset), we used the mini-batch K-means method [55] instead of traditional K-means. Accordingly, we split the set of descriptors into 30 batches. At the end of the clustering step, we obtain k clusters with k centers (c_1, c_2, ... c_k). We then assign each descriptor to the its nearest cluster center.

Instead of dealing with the huge number of descriptors for each document, feature encoding allows obtaining a single vector per image. The used method is VLAD [14]. VLAD is an encoding method that aggregates the residuals of local descriptor at their nearest centers. To do this, we start by determining the centers of the k clusters (c_1, c_2, ... c_k), using the MinBatch K-Means method, for all images. Then we calculate, for each document image, the VLAD vector of the set of descriptors $(x_i)_i$ of the image.

We can represent the corresponding VLAD : V=$(v_{i,j})_{i,j}$ as a matrix whose rows elements dimension is the same as the one of the descriptors. The elements of the descriptor are calculated using:

$$v_{i,j} = \sum_{\substack{i,j \\ Nearest\,(xi) = cj}} (x_i - c_j)$$

After calculating the VLAD vector, we apply two successive normalization steps. The first one corresponds to a power normalization:

$$V = sign\,(V) * |V|^p$$

The second one is an L2 normalization:

$$\mathrm{V} = V/\|V\|_2$$

3.5. Classification

Classification permits to assign a questioned document to the corresponding writer, by calculating similarity between its corresponding features to the ones of reference samples. To do this, we first extract the VLAD vector of the document, then we use the ball tree classifier to find, among the reference documents, the nearest VLAD vector (i.e. vector with highest similarity) to the one of the questioned document. The used ball tree [56] algorithm is an improvement of the KNN. It consists in clustering a set of data points in a multi-dimensional space into a nested set of hyperspheres. The resulting data outcome has a tree-like structure. Using ball tree allows to hugely reduce the calculation time of the classification phase through accelerating the nearest neighbor search.

4. DATASETS

In order to evaluate the performance of our approach, we carried out tests on five handwritten documents datasets as shown in Figure 6. The datasets were chosen to cover a variety of handwriting styles and document types to ensure comprehensive evaluation. In this section, we provide an overview of the used datasets.

4.1. CVL

CVL [57] is a bilingual script database. It comprises the manuscripts of 311 writers. The dataset includes between 5 and 7 manuscripts per writer (6 in English and 1 in German). For each writer, we use one document for the test phase, and the rest for the training phase.

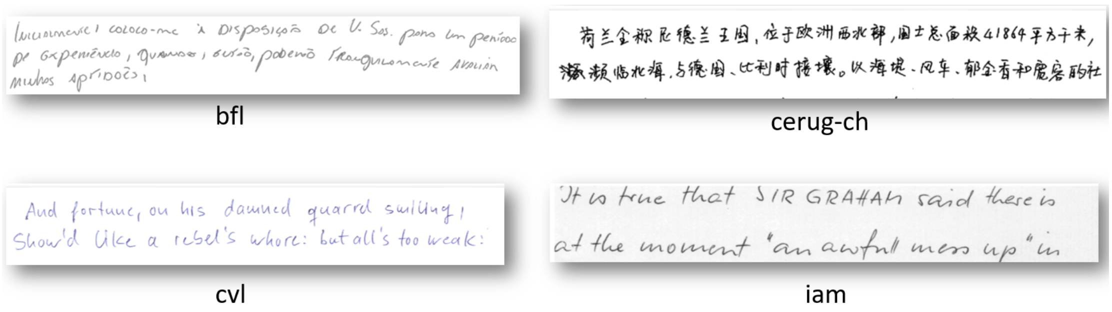

Figure 6. Handwriting samples from the used datasets

4.2. IAM

The IAM database [58] comprises handwriting samples of free text in English. In the first version of the dataset, the 400 participants produced 1066 documents. In our experimental phase, we used the extended version of the IAM dataset. This version contains 1539 documents belonging to 657 participants.

4.3. CERUG

CERUG [59] is a bilingual dataset. The dataset is created with the help of 105 volunteers. Each volunteer produces four manuscript documents. On the first document, the writer copied two fixed paragraphs in Chinese language. The second document is a free Chinese text. On the third document, the participants copy two paragraphs in English. This third document has been split into two pages, each of which contains one paragraph. This split operation allowed to have two English documents. The CERUG-CH and CERUG-EN dataset refer respectively to the documents in Chinese and the ones in English languages of the CERUG dataset.

4.4. Brazilian forensic letter

The Brazilian forensic letter (BFL) [60] is a Portuguese database. It was designed to help the Brazilian forensic experts and federal police in writer identification and verification. This dataset includes the handwritten documents belonging to 315 Brazilian participants. Each participant produced 3 pages, making a total of 945 page documents. All pages are scanned in gray level at 300 dpi resolution.

5. EXPERIMENTS & RESULTS

This section evaluates the effectiveness of the proposed MP-LBP texture descriptor. We employ a two-pronged approach. First, we investigate the impact of varying system parameters on the descriptor's performance. This analysis helps us understand the sensitivity of the descriptor to different configuration settings. Second, we compare the performance of MP-LBP against the original LBP descriptor. This comparison provides a direct assessment of the improvement achieved by our proposed method. Finally, we benchmark the results of our approach against the state-of-the-art texture descriptors to situate its performance. The tests are carried out on the five datasets detailed in section 4.

5.1. Effect of patch size on the system performance

Many studies showed that varying the fragment size can significantly influence the identification rate [24], [41]. Indeed, the fragments are the conciliation between two contradictory constraints: the fragments size must be big enough to include maximum information about the writer style, but must also be too small to include only redundant pattern that can help identify uniquely each individual writer. The evaluation results presented in Figure 7 demonstrate that the score exhibits dependence on the fragment size, but also that the optimal fragment size depends on the nature and size of the used dataset. In fact, the optimal fragment size is 27 pixels for CERUG-EN, CERUG-CH, CVL, and IAM datasets. Whereas it is 31 pixels for BFL.

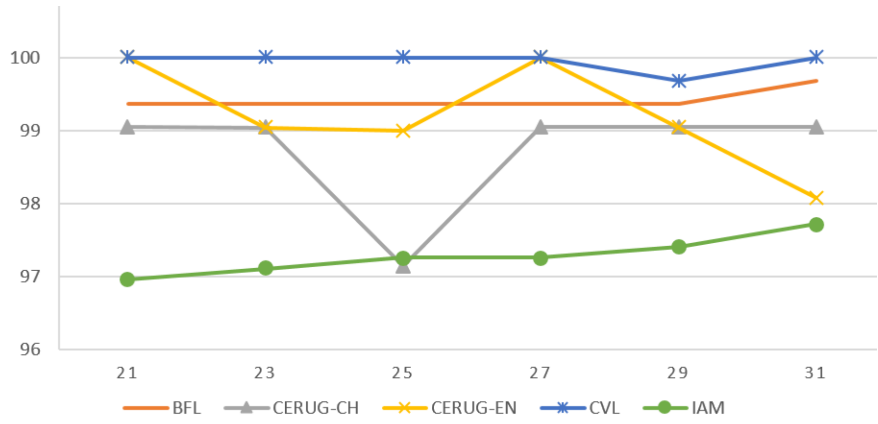

Figure 7. Effect of fragment size on the system performance

5.2. Effect of cluster number on the system performance

The clustering operation consists in grouping similar descriptors into a reduced number of clusters. This operation is performed before calculating the VLAD vectors of the hand written documents. In our approach we used the mini-batch K-means method [55]. The set of descriptors introduced to the clustering process by batches, and the number of batches is fixed to 30 for all the carried out tests. Worth noting that using a big number of clusters requires large memory space and a long calculation time, especially for big datasets. Therefore, a sound cluster number can be a compromise between execution time and identification performance.

In our tests, we used four values of cluster number: k= 64, 128, 256 and 512. The test results are shown in Figure 8. And we can deduce that the system performance is generally insensitive to the number of clusters for the four datasets CERUG-CH, CVL, IAM, and BFL datasets. However, for the CERUG-EN dataset, we observe that the identification rate increases as the cluster number increases: the score went up from 97.1% with k=64 to 100% with k=512. Finally, we observe that the identification rate increases, in general, as the cluster number increases. Nevertheless, the fluctuations in identification rate indicate that the optimal cluster number can only be determined empirically.

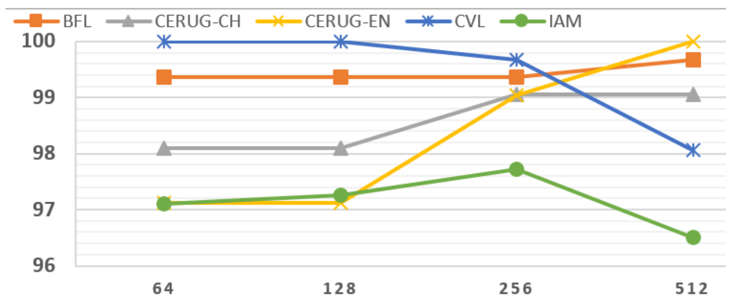

Figure 8. Effect of cluster number on the system performance

5.3. Effect of radius parameter

The radius parameter is the unit distance between the central pixel C and the different neighbors. Figure 9 shows the pattern corresponding to the radius values: R=1, R=2, R=3. We fixed the number of neighbors to P=8. In our study, we used different values of the radius parameter, namely R=3, 5, 7, 9, 10, 11.

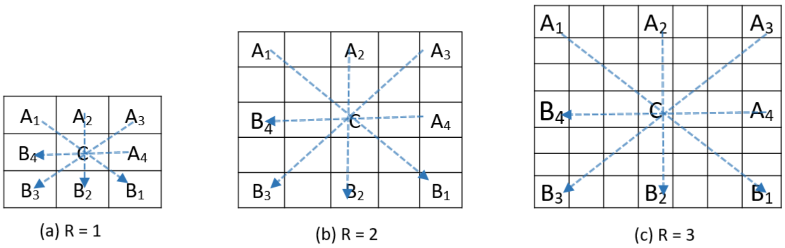

Figure 9. Example of three values of the radius parameter

5.4. Effect of radius size on the system performance

Figure 10 shows that the optimal value of the radius parameter varies depending on the used dataset. Notably, this variability highlights the importance of dataset-specific tuning for achieving optimal results. But in general, the highest scores correspond to a radius parameter comprised between five and nine pixels for the five datasets.

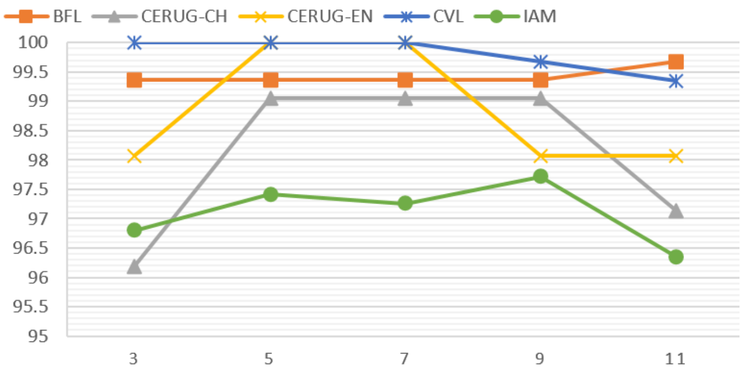

Figure 10. Effect of radius size on the system performance

5.5. Optimal parameter values for the different datasets

The optimal values for the different parameters that yield the best scores vary depending on the dataset used. Table 2 summarizes the optimal values of these parameters. This variability underscores the necessity of tuning parameter settings to each specific dataset for achieving maximum performance.

Table 2. Optimal parameter values patch size, cluster number and radius for the five datasets

Dataset	Top 1 IR (%)	Patch size	Cluster number	Radius
IAM	97.72	31	256	9
CVL	100	21	64	5
CERUG-EN	100	27	512	7
CERUG-CH	99.05	21	512	5
BFL	99.68	31	512	11

5.6. Performance comparison between LBP and MP-LBP

When comparing our MP-LBP texture descriptor's results with those of the LBP, we can affirm that our descriptor's performance is the best in the five datasets. In fact, with our descriptor we reached 100% identification rate for CERUG-EN and CVL. Moreover, for IAM dataset, our method improves the scores with about 6 points. And a less improvement is observed also in the BFL and CERUG-CH datasets, as depicted in Figure 11.

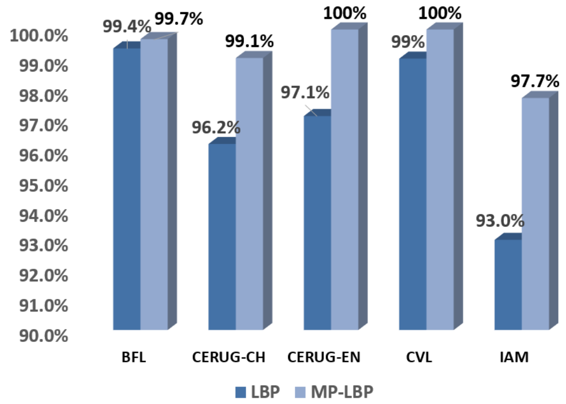

Figure 11. Performance comparison between LBP and MP-LBP

5.7. Comparison with the state-of-the-art works

To verify the performance of our technique with respect to other existing methods, we present in Tables 3 to 7 a performance comparison with several state-of-the-art works. For the IAM dataset, the classification rates achieved by different studies are listed in Table 3, where it can be noted that the score achieved by our approach remains comparable with the best rates obtained on the complete set of 657 writers. The same remark can be deduced for the two databases BFL and CERUG-CN. Indeed, the two Tables 5 and 4 show that the two scores achieved, which are respectively 99.68% and 99.05% are very close to the best identification rates achieved by the other techniques using the two databases BFL and CERUG-CN. The two remaining Tables 6 and 7 present the classification rates obtained by other state-of-the-art works, where we can see that our system achieves the best performance with a 100% identification rate obtained in the two databases CVL and CERUG-CN.

Table 3. Score comparison with state-of-the-art on the IAM dataset

Method	Year	Nbr Writers	Feature-based	Top 1 IR (%)
Bulacu and Schomaker [2]	2007	650	Texture and Codebook	89
Bertolini *et al.* [26]	2013	650	Texture	96.7
Wu *et al.* [44]	2014	657	Texture	98.5
He *et al.* [59]	2015	650	Codebook and Texture	91.1
Khan *et al.* [61]	2017	650	Codebook	97.2
Singh *et al.* [34]	2018	657	Texture	97.62
Khan *et al.* [46]	2019	650	Texture	97.85
Kumar and Sharma [62]	2019	657	Texture	97.5
Chahi *et al.* [47]	2020	657	Texture	97.85
He and Schomaker [63]	2020	657	Deep-learning	96.3
Lai *et al.* [64]	2021	657	Deep-learning	99.5
Semma *et al.* [43]	2021	657	Deep-learning	99.5
Bahram [15]	2021	657	Texture	98.17
Our (MP-LBP)	2023	657	Texture	97.72

Table 4. Score comparison with state-of-the-art on the CERUG-CN dataset

Method	Year	Nbr Writers	Feature-based	Top 1 IR (%)
He *et al.* [59]	2015	105	Texture	90.8
Brink *et al.* [65]	2015	105	Texture	82.7
He *et al.* [59]	2015	105	Codebook	90.84
He *et al.* [59]	2015	105	Codebook and Texture	94.2
Chahi *et al.* [47]	2020	105	Texture	100
Bahram [15]	2021	105	Texture	100
Our (MP-LBP)	2023	105	Texture	99.05

Table 5. Score comparison with state-of-the-art on the BFL dataset

Method	Year	Nbr Writers	Feature-based	Top 1 IR (%)
Kessentini *et al.* [48]	2010	315	Texture	93.02
Bertolini *et al.* [26]	2013	315	Texture	99.2
Kessentini *et al.* [48]	2018	315	Texture	98.41
Bennour *et al.* [35]	2019	315	Codebook	98.33
Semma *et al.* [66]	2022	315	Texture	99.4
Bahram [15]	2022	315	Texture	100
Our (MP-LBP)	2023	315	Texture	99.68

Table 6. Score comparison with state-of-the-art on the CVL dataset

Method	Year	Nbr Writers	Feature-based	Top 1 IR (%)
Siddiqi and Vincent [67]	2010	310	Texture	96.13
Khan *et al.* [61]	2017	310	Codebook	99.6
Kessentini *et al.* [48]	2018	310	Texture	94.83
Khan *et al.* [46]	2019	310	Texture	99.03
Bennour *et al.* [35]	2019	311	Codebook	94.32
Kumar and Sharma [68]	2020	310	Deep-learning	99.35
Lai *et al.* [64]	2020	310	Deep-learning	99.76
He and Schomaker [63]	2020	310	Deep-learning	99.1
Semma *et al.* [66]	2022	315	Texture	99.4
Chahi *et al.* [47]	2020	310	Texture	100
Bahram [15]	2022	310	Texture	100
Our (MP-LBP)	2023	310	Texture	100

Table 7. Score comparison with state-of-the-art on the CERUG-EN dataset

Method	Year	Nbr Writers	Feature-based	Top 1 IR (%)
He *et al.* [59]	2015	105	Code-book et Texture	89.5
He *et al.* [69]	2017	105	Texture (LBPrun)	97.1
Chahi *et al.* [47]	2020	105	Texture (LSTP)	98.1
He and Schomaker [63]	2021	105	Deep Learning	100
He and Schomaker [70]	2021	105	Global-Context Residual RNN	99.1
Our (MP-LBP)	2023	105	Texture	100

6. CONCLUSION

Despite the great progress in automated handwriting analysis during the two last decades, this research area remains an open problem. The handwriting analysis can concern either explicit attributes such as the characters and words, or implicit ones such as writer's identity, historical period, and writer's gender. For each of these attributes, the research community developed many methods in order to solve the address the problem. In this paper, we presented a new texture descriptor MP-LBP. The MP-LBP is a generalization of the LBP texture descriptor. The carried out experiment provide conclusive evidence that our new descriptor outperforms the traditional LBP descriptor for all the five used datasets. This can be justified by the fact that information in our descriptor is not derivable from the conventional LBP. Moreover, the performance of our approach is comparable to one of the state of the art works. For further improvements, and inspired by the LTP descriptor, we intend to evaluate the introduction of a threshold parameter. We also intend to test other point numbers in order to verify the descriptive potential based on sorting 4 or 5 points.

REFERENCES

[1] A. Nosary, L. Heutte, T. Paquet, and Y. Lecourtier, "Defining writer's invariants to adapt the recognition task," in *Proceedings of the International Conference on Document Analysis and Recognition, ICDAR*, 1999, pp. 769–772, doi: 10.1109/ICDAR.1999.791900.

[2] M. Bulacu and L. Schomaker, "Text-independent writer identification and verification using textural and allographic features," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 4, pp. 701–717, 2007, doi: 10.1109/TPAMI.2007.1009.

[3] S. Srihari, S. Cha, H. Arora, and S. Lee, "Individuality of handwriting," *Journal of Forensic Sciences*, vol. 47, no. 4, pp. 1–17, 2002, doi: 10.1520/jfs15447j.

[4] J. D. A.- Fossoul and K. A. Roberts, "Forensic intelligence applied to questioned document analysis: A model and its application against organized crime," *Science and Justice*, vol. 57, no. 4, pp. 314–320, 2017, doi: 10.1016/j.scijus.2017.04.003.

[5] C. Djeddi, S. A. -Maadeed, A. Gattal, I. Siddiqi, L. S. -Meslati, and H. E. Abed, "ICDAR2015 competition on multi-script writer identification and gender classification using 'QUWI' database," in *2015 13th International Conference on Document Analysis and Recognition (ICDAR)*, 2015, pp. 1191–1195, doi: 10.1109/ICDAR.2015.7333949.

[6] A. Semma, Y. Hannad, I. Siddiqi, S. Lazrak, and M. E. Y. E. Kettani, "Feature learning and encoding for multi-script writer identification," *International Journal on Document Analysis and Recognition*, vol. 25, no. 2, pp. 79–93, 2022, doi: 10.1007/s10032-022-00394-8.

[7] R. Plamondon and G. Lorette, "Automatic signature verification and writer identification - the state of the art," *Pattern Recognition*, vol. 22, no. 2, pp. 107–131, 1989, doi: 10.1016/0031-3203(89)90059-9.

[8] H. E. S. Said, T. N. Tan, and K. D. Baker, "Personal identification based on handwriting," *Pattern Recognition*, vol. 33, no. 1, pp. 149–160, 2000, doi: 10.1016/S0031-3203(99)00006-0.

[9] W. Yang, L. Jin, and M. Liu, "DeepWriterID: an end-to-end online text-independent writer identification system," *IEEE Intelligent Systems*, vol. 31, no. 2, pp. 45–53, 2016, doi: 10.1109/MIS.2016.22.

[10] C. Djeddi, L. -S. Meslati, I. Siddiqi, A. Ennaji, H. E. Abed, and A. Gattal, "Evaluation of texture features for offline arabic writer identification," in *2014 11th IAPR International Workshop on Document Analysis Systems*, 2014, pp. 106–110, doi: 10.1109/DAS.2014.76.

[11] V. Christlein and A. Maier, "Encoding CNN activations for writer recognition," in *2018 13th IAPR International Workshop on Document Analysis Systems (DAS)*, 2018, pp. 169–174, doi: 10.1109/DAS.2018.9.

[12] A. Rehman, S. Naz, M. I. Razzak, and I. A. Hameed, "Automatic visual features for writer identification: a deep learning approach," *IEEE Access*, vol. 7, pp. 17149–17157, 2019, doi: 10.1109/ACCESS.2018.2890810.

[13] A. A. -Dmour and R. A. Zitar, "Arabic writer identification based on hybrid spectral-statistical measures," *Journal of Experimental and Theoretical Artificial Intelligence*, vol. 19, no. 4, pp. 307–332, 2007, doi: 10.1080/09528130701228800.

[14] H. Jégou, F. Perronnin, M. Douze, J. Sánchez, P. Pérez, and C. Schmid, "Aggregating local image descriptors into compact codes," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no. 9, pp. 1704–1716, 2012, doi: 10.1109/TPAMI.2011.235.

[15] T. Bahram, "A texture-based approach for offline writer identification," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 8, pp. 5204–5222, 2022, doi: 10.1016/j.jksuci.2022.06.003.

[16] K. Franke et al., "WANDA: a generic framework applied in forensic handwriting analysis and writer identification," in *Design and application of hybrid intelligent systems. Proceedings 3rd International Conference on Hybrid Intelligent Systems (HIS03)*, 2003, pp. 927–938.

[17] S. N. Srihari, B. Srinivasan, and K. Desai, "Questioned document examination using CEDAR-FOX," *Journal of Forensic Document Examination*, vol. 18, no. 2, pp. 1–20, 2007.

[18] B. Arazi, "Handwriting identification by means of run-length measurements," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 7, no. 12, pp. 878–881, 1977, doi: 10.1109/TSMC.1977.4309648.

[19] Z. He, X. You, and Y. Y. Tang, "Writer identification using global wavelet-based features," *Neurocomputing*, vol. 71, no. 10–12, pp. 1832–1841, 2008, doi: 10.1016/j.neucom.2007.10.017.

[20] U. Garain and T. Paquet, "Off-line multi-script writer identification using AR coefficients," in *2009 10th International Conference on Document Analysis and Recognition*, 2009, pp. 991–995, doi: 10.1109/ICDAR.2009.222.

[21] A. Gattal, C. Djeddi, I. Siddiqi, and S. A. -Maadeed, "Writer identification on historical documents using oriented basic image features," in *2018 16th International Conference on Frontiers in Handwriting Recognition (ICFHR)*, 2018, pp. 369–373, doi: 10.1109/ICFHR-2018.2018.00071.

[22] L. Schomaker and M. Bulacu, "Automatic writer identification using connected-component contours and edge-based features of uppercase western script," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 26, no. 6, pp. 787–798, 2004, doi: 10.1109/TPAMI.2004.18.

[23] R. Jain and D. Doermann, "Offline writer identification using k-adjacent segments," in *2011 International Conference on Document Analysis and Recognition*, 2011, pp. 769–773, doi: 10.1109/ICDAR.2011.159.

[24] Y. Hannad, I. Siddiqi, and M. E. Y. E. Kettani, "Writer identification using texture descriptors of handwritten fragments," *Expert Systems with Applications*, vol. 47, pp. 14–22, 2016, doi: 10.1016/j.eswa.2015.11.002.

[25] N. Bendaoud, Y. Hannad, A. Samaa, and M. E. Y. E. Kettani, "Effect of the sub-graphemes' size on the performance of off-line arabic writer identification," *Communications in Computer and Information Science*, vol. 872, pp. 512–522, 2018, doi: 10.1007/978-3-319-96292-4_40.

[26] D. Bertolini, L. S. Oliveira, E. Justino, and R. Sabourin, "Texture-based descriptors for writer identification and verification," *Expert Systems with Applications*, vol. 40, no. 6, pp. 2069–2080, 2013, doi: 10.1016/j.eswa.2012.10.016.

[27] S. Lazrak, A. Semma, N. A. E. Kaab, M. E. Y. E. Kettani, and D. Mentagui, "Writer identification using textural features," *ITM Web of Conferences*, vol. 43, p. 01027, 2022, doi: 10.1051/itmconf/20224301027.

[28] A. J. Newell and L. D. Griffin, "Writer identification using oriented basic image features and the delta encoding," *Pattern Recognition*, vol. 47, no. 6, pp. 2255–2265, 2014, doi: 10.1016/j.patcog.2013.11.029.

[29] A. Gattal, C. Djeddi, I. Siddiqi, A. Bensefia, and K. Saoudi, "Texture feature column scheme for single-and multi-script writer identification," *IET Biometrics*, vol. 10, no. 2, pp. 179–193, 2021, doi: 10.1049/bme2.12010.

[30] Y. Hannad, I. Siddiqi, C. Djeddi, and M. E. Y. E.-Kettani, "Improving Arabic writer identification using score-level fusion of textural descriptors," *IET Biometrics*, vol. 8, no. 3, pp. 221–229, 2019, doi: 10.1049/iet-bmt.2018.5009.

[31] T. Ojala, M. Pietikäinen, and T. Mäenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971–987, 2002, doi: 10.1109/TPAMI.2002.1017623.

[32] Y. Hannad, I. Siddiqi, and M. E. Y. E. Kettani, "Arabic writer identification using local binary patterns (LBP) of handwritten fragments," in *Iberian Conference on Pattern Recognition and Image Analysis*, 2015, pp. 237–244, doi: 10.1007/978-3-319-19390-8_27.

[33] A. Bensefia, A. Nosary, T. Paquet, and L. Heutte, "Writer identification by writer's invariants," in *Proceedings Eighth International Workshop on Frontiers in Handwriting Recognition*, 2002, pp. 274–279, doi: 10.1109/IWFHR.2002.1030922.

[34] P. Singh, P. P. Roy, and B. Raman, "Writer identification using texture features: A comparative study," *Computers and Electrical Engineering*, vol. 71, pp. 1–12, 2018, doi: 10.1016/j.compeleceng.2018.07.003.

[35] A. Bennour, C. Djeddi, A. Gattal, I. Siddiqi, and T. Mekhaznia, "Handwriting based writer recognition using implicit shape codebook," *Forensic Science International*, vol. 301, pp. 91–100, 2019, doi: 10.1016/j.forsciint.2019.05.014.

[36] A. Bensefia, T. Paquet, and L. Heutte, "A writer identification and verification system," *Pattern Recognition Letters*, vol. 26, no. 13, pp. 2080–2092, 2005, doi: 10.1016/j.patrec.2005.03.024.

[37] I. Siddiqi and N. Vincent, "Writer identification in handwritten documents," in *Ninth International Conference on Document Analysis and Recognition (ICDAR 2007)*, 2007, vol. 1, pp. 108–112, doi: 10.1109/ICDAR.2007.4378685.

[38] H. T. Nguyen, C. T. Nguyen, T. Ino, B. Indurkhya, and M. Nakagawa, "Text-independent writer identification using convolutional neural network," *Pattern Recognition Letters*, vol. 121, pp. 104–112, 2019, doi: 10.1016/j.patrec.2018.07.022.

[39] L. Xing and Y. Qiao, "DeepWriter: A multi-stream deep CNN for text-independent writer identification," in *2016 15th International Conference on Frontiers in Handwriting Recognition (ICFHR)*, 2016, pp. 584–589, doi: 10.1109/ICFHR.2016.0112.

[40] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778, doi: 10.1109/CVPR.2016.90.

[41] A. Semma, Y. Hannad, and M. E. Y. E. Kettani, "Impact of the CNN patch size in the writer identification," *Networking, Intelligent Systems and Security*, vol. 237, pp. 103–114, 2022, doi: 10.1007/978-981-16-3637-0_8.

[42] A. Semma, S. Lazrak, Y. Hannad, M. Boukhani, and Y. E. Kettani, "Writer identification: the effect of image resizing on CNN performance," *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, vol. 46, pp. 501–507, 2021, doi: 10.5194/isprs-Archives-XLVI-4-W5-2021-501-2021.

[43] A. Semma, Y. Hannad, I. Siddiqi, C. Djeddi, and M. E. Y. E. Kettani, "Writer identification using deep learning with FAST keypoints and harris corner detector," *Expert Systems with Applications*, vol. 184, 2021, doi: 10.1016/j.eswa.2021.115473.

[44] X. Wu, Y. Tang, and W. Bu, "Offline text-independent writer identification based on scale invariant feature transform," *IEEE Transactions on Information Forensics and Security*, vol. 9, no. 3, pp. 526–536, 2014, doi: 10.1109/TIFS.2014.2301274.

[45] A. Chahi, I. El khadiri, Y. El merabet, Y. Ruichek, and R. Touahni, "Block wise local binary count for off-Line text-independent writer identification," *Expert Systems with Applications*, vol. 93, pp. 1–14, 2018, doi: 10.1016/j.eswa.2017.10.010.

[46] F. A. Khan, F. Khelifi, M. A. Tahir, and A. Bouridane, "Dissimilarity gaussian mixture models for efficient offline handwritten text-independent identification using SIFT and RootSIFT descriptors," *IEEE Transactions on Information Forensics and Security*, vol. 14, no. 2, pp. 289–303, 2018, doi: 10.1109/TIFS.2018.2850011.

[47] A. Chahi, Y. E. Merabet, Y. Ruichek, and R. Touahni, "Local gradient full-scale transform patterns based off-line text-independent writer identification," *Applied Soft Computing*, vol. 92, 2020, doi: 10.1016/j.asoc.2020.106277.

[48] Y. Kessentini, S. B. Abderrahim, and C. Djeddi, "Evidential combination of SVM classifiers for writer recognition," *Neurocomputing*, vol. 313, pp. 1–13, 2018, doi: 10.1016/j.neucom.2018.05.096.

[49] T. Bahram, "A connected component-based approach for text-independent writer identification," in *2019 6th International Conference on Image and Signal Processing and their Applications (ISPA)*, 2019, pp. 1–6, doi: 10.1109/ISPA48434.2019.8966903.

[50] Z. Wang and A. C. Bovik, "A universal image quality index," *IEEE Signal Processing Letters*, vol. 9, no. 3, pp. 81–84, 2002, doi: 10.1109/97.995823.

[51] C. Harris and M. Stephens, "A combined corner and edge detector," in *Alvey Vision Conference*, 1988, pp. 147–151, doi: 10.5244/C.2.23.

[52] J. A. R. -Serrano and F. Perronnin, "Local gradient histogram features for word spotting in unconstrained handwritten documents," in *International Conference on Frontiers in Handwriting Recognition*, 2008, pp. 7–12.

[53] T. N. Tan, "Written language recognition based on texture analysis," *IEEE International Conference on Image Processing*, vol. 2, pp. 185–188, 1996, doi: 10.1109/icip.1996.560633.

[54] I. Siddiqi and N. Vincent, "Descripteurs locaux de forme pour la reconnaissance du scripteur," in *Colloque International Francophone sur l'Ecrit et le Document*, 2008, pp. 157–162.

[55] D. Sculley, "Web-scale k-means clustering," in *Proceedings of the 19th International Conference on World Wide Web*, 2010, pp. 1177–1178, doi: 10.1145/1772690.1772862.

[56] S. M. Omohundro, "Five balltree construction algorithms," *International Computer Science Institute*, Berkeley, California, pp. 1–22, 1989.

[57] F. Kleber, S. Fiel, M. Diem, and R. Sablatnig, "CVL-DataBase: an off-line database for writer retrieval, writer identification and word spotting," in *2013 12th International Conference on Document Analysis and Recognition*, 2013, pp. 560–564, doi: 10.1109/ICDAR.2013.117.

[58] U. V. Marti and H. Bunke, "The IAM-database: An English sentence database for offline handwriting recognition," *International Journal on Document Analysis and Recognition*, vol. 5, no. 1, pp. 39–46, 2003, doi: 10.1007/s100320200071.

[59] S. He, M. Wiering, and L. Schomaker, "Junction detection in handwritten documents and its application to writer identification," *Pattern Recognition*, vol. 48, no. 12, pp. 4036–4048, 2015, doi: 10.1016/j.patcog.2015.05.022.

[60] C. O. A. Freitas, L. S. Oliveira, R. Sabourin, and F. Bortolozzi, "Brazilian forensic letter database," *11th International Workshop on Frontiers on Handwriting Recognition, Montreal Canada*, pp. 1–6, 2008.

[61] F. A. Khan, M. A. Tahir, F. Khelifi, A. Bouridane, and R. Almotaeryi, "Robust off-line text independent writer identification using bagged discrete cosine transform features," *Expert Systems with Applications*, vol. 71, pp. 404–415, 2017, doi: 10.1016/j.eswa.2016.11.012.

[62] P. Kumar and A. Sharma, "DCWI: Distribution descriptive curve and cellular automata based writer identification," *Expert Systems with Applications*, vol. 128, pp. 187–200, 2019, doi: 10.1016/j.eswa.2019.03.037.

[63] S. He and L. Schomaker, "FragNet: writer identification using deep fragment networks," *IEEE Transactions on Information Forensics and Security*, vol. 15, pp. 3013–3022, 2020, doi: 10.1109/TIFS.2020.2981236.

[64] S. Lai, Y. Zhu, and L. Jin, "Encoding pathlet and SIFT features with bagged VLAD for historical writer identification," *IEEE Transactions on Information Forensics and Security*, vol. 15, pp. 3553–3566, 2020, doi: 10.1109/TIFS.2020.2991880.

[65] A. A. Brink, J. Smit, M. L. Bulacu, and L. R. B. Schomaker, "Writer identification using directional ink-trace width measurements," *Pattern Recognition*, vol. 45, no. 1, pp. 162–171, 2012, doi: 10.1016/j.patcog.2011.07.005.

[66] A. Semma, S. Lazrak, Y. Hannad, and M. E. Y. E. Kettani, "Writer identification using VLAD encoding of the histogram of gradient angle distribution," *E3S Web of Conferences*, vol. 351, 2022, doi: 10.1051/e3sconf/202235101073.
[67] I. Siddiqi and N. Vincent, "Text independent writer recognition using redundant writing patterns with contour-based orientation and curvature features," *Pattern Recognition*, vol. 43, no. 11, pp. 3853–3865, 2010, doi: 10.1016/j.patcog.2010.05.019.
[68] P. Kumar and A. Sharma, "Segmentation-free writer identification based on convolutional neural network," *Computers and Electrical Engineering*, vol. 85, 2020, doi: 10.1016/j.compeleceng.2020.106707.
[69] S. He and L. Schomaker, "Writer identification using curvature-free features," *Pattern Recognition*, vol. 63, pp. 451–464, 2017, doi: 10.1016/j.patcog.2016.09.044.
[70] S. He and L. Schomaker, "GR-RNN: Global-context residual recurrent neural networks for writer identification," *Pattern Recognition*, vol. 117, 2021, doi: 10.1016/j.patcog.2021.107975.

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